# Extended Dependency Tree-HMM for Non-Rectangular Sub-Images Modeling

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**Abstract**— This work is motivated by the need of evaluating the likelihood probability on sub-images of not necessarily rectangular shape in some frameworks. For this purpose, we propose an alternative of Dependency Tree- HMM that allows the four traditional interactions between neighboring pixels instead of just two. To demonstrate the accuracy of the proposed model, we provide some classification results performed on high resolution aerial images.

**Index Terms**— Hidden Markov Models (HMM), Dependency Tree- HMM, Sub-Image Modeling.

## 1. Introduction

Pixel-wise approaches for image classification are usually not suitable to solve problems often encountered in remote sensing applications [5, 6]. They result in a disgusting salt and pepper effect. To overcome the drawback of such approaches, more elaborated methods classify each pixel by taking into account some of its neighboring pixels, usually by computing a similarity measure ( likelihood probability for instance) [10]. In most cases, this computation concerns pixels contained in square windows centered at the pixel to classify. However, in some stochastic image modeling frameworks, one may have to evaluate likelihood probabilities on non-rectangular windows, like in [1]. In this work, we propose to extend the so-called dependency tree-hidden Markov model (DT-HMM) proposed in [2] to make possible such computation by allowing the four directional interactions between neighboring pixels instead of just two. This allows one to approximate the genuine 2D-HMM likelihood probability of observing the data contained in circular-like shaped windows or image blocks while maintaining the linear complexity of the traditional 1D-HMM. It was proven in some previous research works [3] that the average value of the likelihood probability computed according to a relatively small number of random dependency trees constitutes a good estimate of the authentic likelihood probability.

The reminder of the paper is organized as follows: section 2 summarizes some previous works where likelihood probability was evaluated on square windows, and shows up the importance of adopting sub-images of different shapes instead of square ones. Section 3 gives an overview about the classical DT-HMM and introduces the EDT-HMM. To validate our theoretical formalism, we show some results obtained on real world high resolution aerial images using the classification scheme proposed in [4]. Future improvements and conclusion remarks are given in section 5.

## 2. Evaluation Windows for Image Modeling

Achieving a statistical classification at pixel level is a difficult ill-posed problem in pattern recognition; most methods evaluate likelihood probability over square windows of the same size [10], which is chosen experimentally. Two particular examples of image classification at pixel level would be fabric defects detection or aerial image indexing. Such problems do not just require the segmentation of the image into distinctive regions which may be performed by unsupervised algorithms such as EDISON [16, 17], but the identification of image pixels. Obviously, such a classification subsumes segmentation but it does not lead necessarily to a segmentation of the whole image. In this scope, unsupervised algorithms are known to be more suitable to segment an image into regions. However, supervised algorithms are required to achieve the identification. In fact, good classifiers apply a filtering and/or segmentation as pre-processing step before carrying out the supervised classification. Such classifiers affect then each pixel to its appropriate class after evaluating likelihood probability on a square window centered at that pixel. Adopting windows aims to take account of contextual information or/and some texture characteristics that cannot be derived from a lonely pixel. The main issue of such a classification scheme is how to pick an appropriate window size; in general, the bigger is the window, the more accurate is the decision. However, a window may be heterogeneous since it may include pixels belonging to more than one class. To take advantage of the preprocessing step (segmentation or/and filtering), one has to restrict window pixels to those belonging to the same class than that of the pixel to identify.

In [14], the authors combine various texture classification methods over multiple square windows of different sizes to detect fabric defects. Their classifier integrates various texture features computed on square windows. In [10], texture image is divided into rectangular blocks of the same size and affect pixels of a same block to the same class.

A wide variety of texture feature extraction methods have been proposed in the computer vision literature [15]. Their performance depends basically on the processing they apply, the neighborhood of pixels over which they are evaluated (window size and shape) and the texture features. When dealing with these methods, one big issue must be addressed: the determination of the window size and shape. Although many studies regarding the performance of the different families of texture extraction methods, only few dealt with the issue of determining the optimal window size [8, 9, 15]. The influence of the window size and shape on classifiers performance was studied in [7] where it has been shown that texture characterization is influenced much more by window size than its shape. Commonly, the window size is defined experimentally depending on the method.

In [4], we proposed a new scheme for land cover classification that advantageously combines an unsupervised segmentation and a statistical recognition. From segmentation results, we suggested to classify each pixel by computing likelihood probability over a particular neighborhood containing pixels surrounding the one to be identified and belonging to its same region. Unlike [10], adopting rectangular windows is not affordable here. Indeed, taking account of heterogeneous pixels within the same window would definitely introduce a bias in both learning and retrieval processes and falsify then the indexing.

## 3. Dependency Tree- HMM Extension

Markov models (Markov Random Fields, Hidden Markov Fields, Hidden Markov Models, Hidden Markov Trees…) were extensively and successfully used for texture modeling and segmentation [11]. This is majorly due to their ability to model contextual dependencies and noise absorption [12]. However, their performance depends widely on the model architecture: genuine 2D-models yield better results but exhibits much higher computational complexity [12]. In general, the more complex is the model, the better are the performances.

Nevertheless, for computational complexity reasons, several approaches consider linear models like HMM even if such a model is not suited for two-dimensional data [13]. More elaborated approaches resort to 2D-models with simplifying assumption. One simplifying assumption that provides good results with a linear complexity is that assumed in DT-HMM [2][3]: one site (image pixel) may depend on either the horizontal or vertical predecessor, but not on both the same time.

The extension of DT-HMM in this work is motivated by two reasons:

- The need to compute likelihood probability on non-rectangular shaped windows of different sizes.
- The need to adopt central pixel (to be labeled) as the dependency tree root since the root shows more interactions with neighbors than other pixels do.

Before describing our model principles, let us define the applicability conditions of the EDT-HMM model on a window $w$ with respect to root $r$ .

The window $w$ must fit the following condition:

- For each site $s$ of $w$ , $s$ must have at least one neighbor $v \in N_s$ that belongs to $w$ and fulfills: $\|v,r\| < \|s,r\|$ where $N_s$ is the 4-neighborhood of $s$ and $\| \ \|$ is the Euclidean distance.

Let $w$ be a window verifying the condition above, and let $r$ be the center of the window and $Y_r = \{y_s / s(i,j) \in w\}$ be the set of features vectors (RGB for instance) of pixels inside $w$ . $Y_r$ is then the observable process. Let $X$ be the hidden process.

The likelihood probability is given by:

$$P(Y_r/\lambda) = \sum_X P(Y_r/X,\lambda)P(X/\lambda) \qquad (1)$$

Unlike DT-HMM, where each pixel may have a predecessor chosen between two directions, in the EDT-HMM modeling, a pixel $s$ may have a predecessor $v$ chosen randomly from the 4-Neighborhood (up, down, right or left) and verifying the Euclidean distance property. Note that, the neighborhood directions of all pixels of $w$ define a tree structure $T$ like depicted in figure 1. We note $T(s) = v$.

The likelihood probability to observe $Y_r$ given the parameters of the DT-HMM $\lambda(\pi, A, B)$ can be approximated as follows:

$$P(Y_r/\lambda) \approx \sum_T \sum_X \left\{ \prod_{s\in w} P(y_s/x_s,\lambda)P(x_s/T,\lambda) \right\} \quad (2)$$

In this paper, we propose to evaluate the likelihood on a set of random dependency trees $\tau$ . The previous equation becomes:

$$P(Y_r/\lambda) \approx \sum_{T\in\tau} \sum_X \left\{ \prod_{s\in w} P(y_s/x_s,\lambda)P(x_s/T,\lambda) \right\} \quad (3)$$

To compute the likelihood probability of equation 3, we define the backward function $\beta_i(s)$ representing the probability of observing the data contained in the sub-tree of $T$ with $s$ as a root starting from the hidden state $i$.

$$\beta_i(s) = \begin{cases} b_i(y_s) & \text{if } s \text{ is a leaf} \\ b_i(y_s) \prod_{T(v)=s} a_{ij}\beta_j(v) & \text{otherwise} \end{cases} \qquad (4)$$

Note that the likelihood probability of equation 3 can be evaluated as follows for each dependency tree $T$:

$$p(Y_r/T,\lambda) = \sum_{i=1}^{N} \pi_i \beta_i(r) \qquad (5)$$

This computation exhibits a reasonable complexity (linear with window size).

The extension of the DT-HMM only concerns likelihood probability computation and Viterbi decoding whereas learning is performed the same way as in DT-HMM context.

The *Viterbi* decoding process can be achieved in a similar way to the likelihood probability computation. In this work, we only resort to likelihood probability computation.

On the other hand, learning is performed via an iterative way the same as for the DT-HMM model, since the parameters are the same:

- Initialize model parameters.
- Choose a random dependency tree $T$ as described above (respecting the Euclidean distance constraint).
- Perform learning as in a linear framework (like in 1D-HMM).

## 4. Experiments

To validate the theoretical formalism proposed in the previous section, we provide here some experimental results obtained on real world high resolution images from RGD74-75 database [18] (Fig. 1) using the classification scheme proposed in [4].

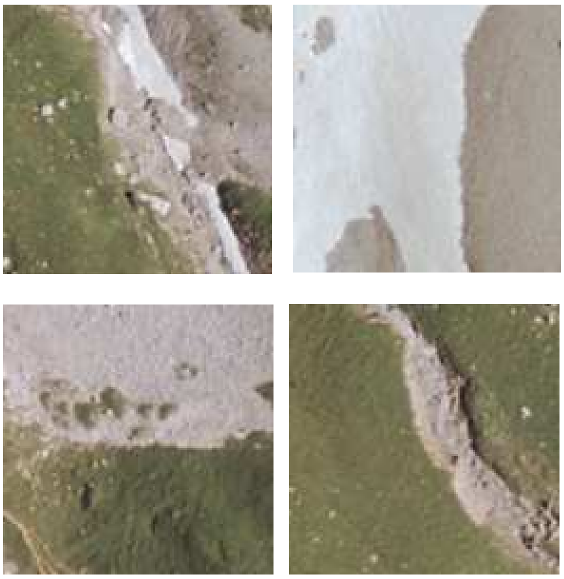

Figure 1: Examples of aerial images from RGD 73-74

Our objective is to locate snow and vegetation in the images. As preprocessing, we segmented each aerial image into homogenous regions using *EDISON* software. Then, we identify each pixel by computing likelihood probability over circular-like windows that fit the applicability conditions of the proposed EDT-HMM. This allows us to perform the computing simultaneously on different machines. Finally, we corrected the indexing by merging the pixels belonging to the same region by affecting them to the predominating class (Fig. 2).

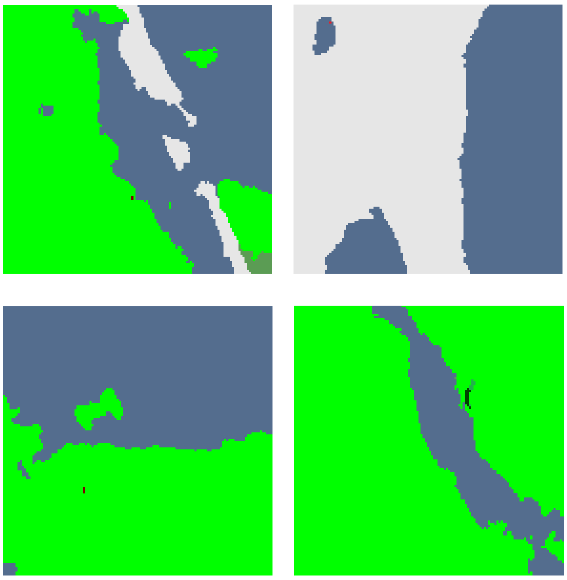

Figure 2: Classification results (vegetation in green and snow in white)

## 5. Conclusion

Most pixel-based classifiers adopt rectangular windows to identify image pixels. To advantageously take account of pre-processing steps like filtering and segmentation, one should exclude some neighboring pixels from window patches. Since current statistical algorithms are not appropriate to evaluate likelihood probability on such sub-images, we proposed an alternative of DT-HMM that makes such a computation affordable within a linear computational complexity. Moreover, our approach gives one the opportunity to perform the classification process on multi- processor mode; this considerably reduces the processing time. The results performed on real world high resolution aerial images, presented in this paper confirm the validity of our modeling.

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